Iowa's Experience with "Road Diet" Measures: Impacts on Crash Frequencies and Crash Rates Assessed Following a Bayesian Approach

Michael D. Pawlovich, Ph.D., P.E. (corresponding author)
Iowa Department of Transportation, Office of Traffic and Safety
800 Lincoln Way
Ames, Iowa 50010
P: (515) 239-1428
F: (515) 239-1891
Michael.Pawlovich@dot.iowa.gov

Wen Li, M.S.
Graduate Research Assistant
Iowa State University, Department of Statistics
102 Snedecor Hall
Ames, Iowa 50011
P: (515) 294-3440
F: (515) 294-4040
shirley@iastate.edu

Alicia Carriquiry, Ph.D.
Iowa State University, Department of Statistics
102 Snedecor Hall
Ames, Iowa 50011
P: (515) 294-7782
F: (515) 294-4040
alicia@iastate.edu

Tom Welch, P.E.
Iowa Department of Transportation, Office of Traffic and Safety
800 Lincoln Way
Ames, Iowa 50010
P: (515) 239-1428
F: (515) 239-1891
Tom.Welch@dot.iowa.gov

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ABSTRACT

A Bayesian data analysis to assess the reduction in crash history due to "road diets" in Iowa was conducted by the Iowa State University Department of Statistics in cooperation with Iowa Department of Transportation Office of Traffic and Safety (TAS). The study utilized monthly crash data and estimated volumes obtained from TAS for 30 sites, 15 treatment and 15 control, over 23 years (1982-2004). The sites had volumes ranging from 2,030 to 15,350 during that timespan and were largely located in smaller urbanized areas.

The main research objective was to assess whether "road diets" appear to result in crash reductions on Iowa roads. To meet the objective we analyzed crash data at each site before and after the conversions were completed. Given the random and rare nature of crash events, we fitted a hierarchical Poisson model to crashes, where the log mean was expressed as a piece-wise linear function of time period, seasonal effects, and a random effect corresponding to each site. Estimation of model parameters was conducted within a Bayesian framework. Results indicate a 25.2% reduction in crash frequency per mile and an 18.8% reduction in crash rate. This differs from a previous, much publicized study which reported a 6% reduction in crash frequency per mile and an insignificant indication for crash rate effects. The results from the Iowa study fit practitioner experience and agree with another Iowa study utilizing a simple before/after approach on the same sites.

INTRODUCTION

A Bayesian data analysis to evaluate the reduction in crash history due to "road diets" in Iowa was conducted by the Iowa State University Department of Statistics in cooperation with Iowa Department of Transportation Office of Traffic and Safety (TAS) (1). The study utilized monthly crash data and estimated volumes obtained from TAS for 30 sites, 15 treatment (sites 1 through 15) and 15 control (sites 18 through 32), over 23 years (1982-2004). The sites had volumes ranging from 2,030 to 15,350 during that timespan (1982-2004) and were largely located in smaller urbanized areas. Table 1 displays more detailed site descriptions and the year 2000 city populations and traffic volumes. Further discussion of the data is presented later.

TABLE 1 Site Locations

SID	CITY	LITERAL	CIPOP 2000	ADT 2000
1	Storm Lake	Iowa 7 from Lake Ave. to Lakeshore Dr.	10,076	7,503
2	Clear Lake	US 18 from N 16 St. W to N 8th St.	8,161	10,403
3	Mason City	Iowa 122 from West intersection of Birch Drive to a Driveway	29,172	7,800
4	Osceola	US 34 from Corporate limits on east side to where highway divides to 4 lanes on west side	4,659	8,172
5	Manchester	Iowa 13 from River St. to Butler St.	5,257	9,400
6	Iowa Falls	US 65 from City Limits - ? to Park Ave.	5,193	10,609
7	Rock Rapids	Iowa 9 from S Greene St. to Tama St.	2,573	4,766
8	Glenwood	US 275 from MP 36.2 to MP 37.42	5,358	6,410
9	Des Moines	Beaver Ave from Urbandale Ave. to Aurora Ave.	198,682	13,695
10	Council Bluffs	US 6 from McKenzie Ave. west 1300 ft.	58,268	11,000
11	Blue Grass	Old US 61 from Oak Lane to 400' W of Terrace Drive	1,169	9,155
12	Sioux Center	US 75 from 200' South of 10th St. S. to 250' North of 9th St. NW	6,002	8,942
13	Indianola	Iowa 92 from South R St. to Jct. of US 65/69	12,998	13,288
14	Lawton	US 20 from 100' east of Co. Rd. Eastland Ave. to 1130' West of Co. Rd. Emmet Ave.	697	9,237

15	Sioux City	Transit Ave. from Vine Ave. to just west of Paxton St. at curve	85,013	9,608
18	Storm Lake	Iowa 7 from Lake Ave. to Barton St	10,076	8,790
19	Le Mars	US 75 from 0.01 miles north of 3rd St NW to 0.36 miles SW of 12th St SW	9,237	10,880
20	Cedar Falls	Green Hill Road from 0.10 miles east of IA 58 to 0.09 miles west of Cedar Heights Dr.	36,145	2,768
21	Jefferson	Iowa 4 from National Ave to 0.13 miles north of 250th Ave	4,626	5,685
22	Harlan	Iowa 44 from US 59 to 6th St	5,282	6,981
23	Norwalk	Iowa 28 from 0.03 miles south of Gordon Ave to 0.04 miles south of North Ave	6,884	7,679
24	Belmond	US 69 from 0.38 miles north of Main St to 0.58 miles south of Main St	2,560	3,734
25	Harlan	Iowa 44 from US 59 to 6th St	5,282	6,981
26	Des Moines	Hickman Road - 40th Place east to 0.07 miles west of W 18th St	198,682	13,953
27	Ames	13th Street from 0.09 miles east of Stange Road to 0.07 miles west of Crescent Circle Dr.	50,731	10,711
28	Mapleton	Iowa 141 from 0.02 miles north of Sioux St. to 0.08 miles south of Oak St.	1,322	3,007
29	Algona	US 169 from 0.07 miles south of US 18 to 0.23 miles south of Irvington Rd.	5,741	7,263
30	Oskaloosa	Iowa 92 from 0.12 miles east of IA 432 to 0.07 miles west of Hillcrest Dr	10,938	11,143
31	Merrill	US 75 from 0.05 miles north of 2nd St to 0.18 miles north of Jackson St	754	7,774
32	Sioux City	S. Lakeport from 4th Ave to Lincoln Way	85,013	15,333

The main goal of the study was to assess the before/after impacts of "road diets" in Iowa. Given the random and rare nature of crash events, the monthly nature of the data, and apparent seasonal effects on the number of crashes, a hierarchical Poisson model where the log mean was expressed as a piece-wise linear function of time period, seasonal effects, and a random effect corresponding to each site was fitted to the crash frequencies. We adopted a Bayesian approach for estimating model parameters and drawing inferences.

Results indicate a 25.2% reduction in crash frequency per mile and an 18.8% reduction in crash rate. This differs from a previous, much publicized study (2,3,4) which reported a 6% reduction in crash frequency per mile and an insignificant indication for crash rate effects. The results from the Iowa study fit practitioner experience and agree with another Iowa study utilizing a simple before/after approach on the same sites (5).

LITERATURE REVIEW

"Road diets" have been implemented for numerous years. The earliest "road diet" for our study was completed in 1993. Another source mentions road diets in the mid-1970s and the 1980s (6). Despite this, very little formal research has been conducted on the safety impacts of "road diets", the most notable being relatively recent (2,3,4). However, several studies have mentioned the operational impacts of "road diets". A review of these studies can be found by referencing Knapp (7). The general consensus of these studies agree that under most average daily traffic (ADT) conditions tested, "road diets" have minimal effects on vehicle capacity, because left-turning vehicles are moved into a common two-way left-turn lane. However, if road diets are used for the roads with ADTs above approximately 20,000 vehicles, there is a high probability that traffic congestion will increase to the point of diverting traffic to alternate routes (2,3,4). An Iowa study for one site found that the 85th percentile free flow speed reduced 4 or 5 mph and the percentage of vehicles traveling more than 5 mph over the speed limit dropped by 30 percent after implementation of the four-lane to three-lane conversion (8).

Figure 1 (2,3,4) shows an example "road diet", implemented by reallocating the existing space, while leaving the overall area unchanged (2,3,4).

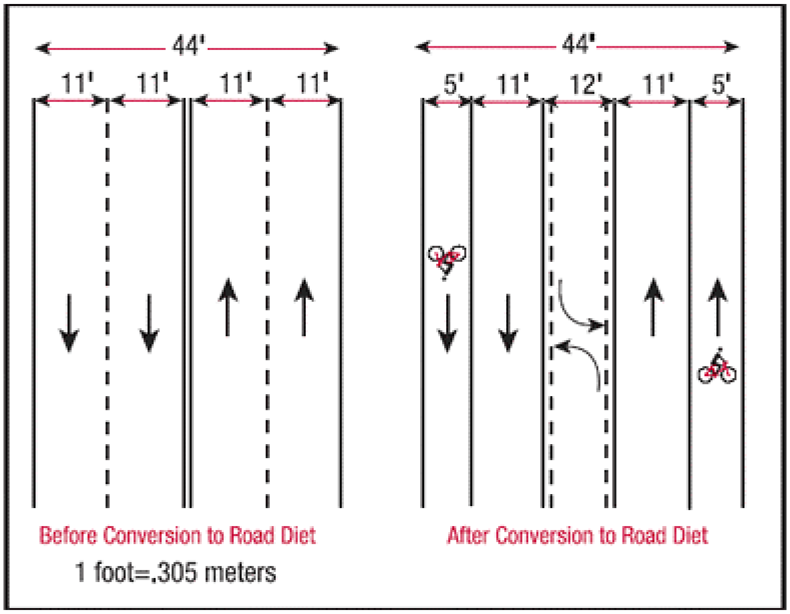


FIGURE 1 Example Road Diet (2,3,4).

"Road diets" offer potential benefits to both vehicles and pedestrians. On a four-lane street, drivers change lanes to pass slower vehicles (such as vehicles stopped in the left lane waiting to make a left turn). In contrast, drivers' speeds on two-lane streets are limited by the speed of the lead vehicle. Thus, road diets may reduce vehicle speeds and vehicle interactions during lane changes, which potentially could reduce the number and severity of vehicle-to-vehicle crashes. Pedestrians may benefit because they have fewer lanes of traffic to cross, and because motor vehicles are likely to be moving more slowly (2,3,4).

The use of Bayesian approaches to highway safety research began with the introduction of empirical Bayes (EB) into the field by Hauer and colleagues. Since then, much research using EB has emerged (9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29) and EB has become a mainstream for researchers, to the point where two recent syntheses (30,31) have discussed the approach and two software FHWA efforts, the Interactive Highway Safety Design Module (IHSDM) and the Comprehensive Highway Safety Improvement Model (CHSIM)/SafetyAnalyst, are primarily based on EB principals (26). The current Highway Safety Manual (HSM) development effort (32) utilizes much EB research as a basis. Hauer's 1997 book directly addressed before/after studies, comparing the EB approach to the classical naïve and classical comparison-group methods (23). Clearly, EB is at the forefront for traffic safety research and will be for years.

However, comparatively recently, full Bayesian (FB) approaches have begun to be explored by traffic safety researchers. Beginning with computer and methodological advances in the early 1990s, the feasibility of full Bayesian applications began to be explored for transportation-related research (33,34). More recently, full Bayesian applications have emerged within highway safety research (35,36,37,38,39,40,41,42,43,44,45,46). Much like EB, FB is gaining wider acceptance throughout the highway safety community; however, broad application of the approach may be years away as modeling techniques are explored and refined. Based on previous and ongoing FB-related work within Iowa (40), we chose the FB approach as the basis for our analysis of Iowa "road diet" experience.

Some of the FB literature mentions comparisons with EB; however, in the main they touch lightly upon the issue. Our choice of FB was based on prior Iowa experience applying the FB approach. As the objective of this research was not to compare EB to FB, we refer interested readers to a widely distributed whitepaper by Carriquiry and Pawlovich (47) available at http://www.dot.state.ia.us/crashanalysis/eb_fb_comparison.htm.

FURTHER SITE AND DATA DESCRIPTION

Shown in Table 2 as COMPYEAR, each treatment site had different known intervention dates; therefore, the number of before and after crash records varied from site to site as the available data ranged in date from 1982-2004. The crash data and volume data for each site were obtained on a monthly basis from 1982-2004, except for site 20 which wasn't constructed until 1993. To obtain the crash data, visual inspection of the available data were made within a Geographic Information System (GIS) and those crashes appearing along the road were exported to file. The volume data were obtained similarly by beginning with visual selection of the sites within a GIS and export to file. TAS has 6 years (2001-2003) of roadway inventory data, which includes traffic volumes, available and factors available to estimate earlier yearly volumes. Other factors exist to estimate monthly volumes by type of facility. These monthly volume data for the 23 years were estimated for each site using custom SAS (SAS Institute Inc., Cary, NC) code to apply these factors. The lengths for the sites were derived directly from the GIS-based mapping. Later, additional custom SAS code was used to parse the crash data by month, merge these data with the volume data, and develop a consolidated database for all locations.

Individual control sites were matched to each treatment site to provide a control sample similar to the treatment sample; these matches are shown in Table 2 using columns SID (the site ID) and YID (the paired ID). The treatment sites are indicated by having 3 lanes, as opposed to 4 for the control sites.

TABLE 2 Site Descriptive Information

SID	YID	ROUTE	LANES	LENGTH	COMPYEAR
1	18	IA 7	3	1.41	1993
2	19	US 18	3	1.51	2003
3	20	IA 122	3	1.78	2001
4	21	US 34	3	2.04	2001
5	22	IA 13	3	0.35	2001
6	23	US 65	3	1.23	2002
7	24	IA 9	3	0.35	1998
8	25	US 275	3	1.09	1998
9	26	Local	3	1.19	1999
10	27	US 6	3	0.20	2000
11	28	Local	3	0.72	1999
12	29	US 75	3	1.52	1999
13	30	IA 92	3	1.57	1999
14	31	US 20	3	0.64	2000

15	32	Local	3	0.77	2000
18	1	IA 7	4	0.71	1993
19	2	US 75	4	1.80	2003
20	3	Local	4	1.80	2001
21	4	IA 4	4	2.40	2001
22	5&8	IA 44	4	1.20	2001
23	6	IA 28	4	0.80	2002
24	7	US 69	4	0.90	1998
25	5&8	IA 44	4	1.20	1998
26	9	Local	4	1.50	1999
27	10	Local	4	0.33	2000
28	11	IA 141	4	0.70	1999
29	12	US 169	4	2.00	1999
30	13	IA 92	4	1.50	1999
31	14	US 75	4	0.50	2000
32	15	Local	4	1.20	2000

Figure 2 below shows the monthly crash density at two of the paired study sites. The y-axis is number of crashes and the x-axis is month. The vertical line in each plot marks the time at which the intervention was completed. In the plot corresponding to the matched control site (site 26), the vertical line was placed at the month during which the intervention was completed at the treatment site. The solid line in each graph is a smooth estimate of the number of crashes over time for each site. The smooth curve was obtained by fitting a non-parametric local polynomial regression with optimal bandwidth (48). We fitted the non-parametric regression model to explore the form of the Poisson regression to be fitted in later analyses. Because the length of the site varied across sites (from a low of 0.24 miles to a high of 2.53 miles) the number of monthly crashes is not strictly comparable across sites in the graphs presented in Figure 2.

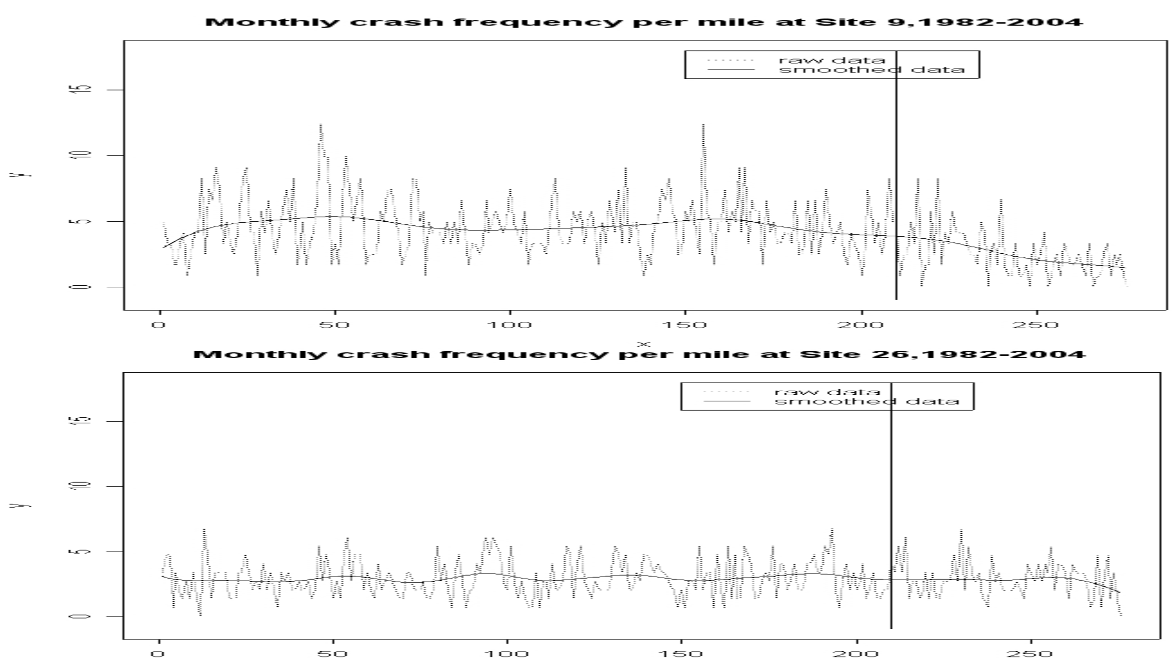


FIGURE 2 Observed and Smoothed Estimated Monthly Crash Density For a Sample Pair of Sites.

Figure 3 explores the potential differences between treated and control sites for the example pair of sites. The plot has three curves: the monthly crash rate (crashes/HMVMT) for treated sites, the monthly crash rate at control sites, and the difference in monthly crash rate between the control and the treated sites (monthly crash rate of treated group – monthly crash rate of control group, solid green line). In this graph, the green line represents the difference in crash rate between treatment and control sites for each month. It appears that the difference is negative more often after intervention than before. And, the general trend of the site-specific crash frequency, now, is clear from the plots.

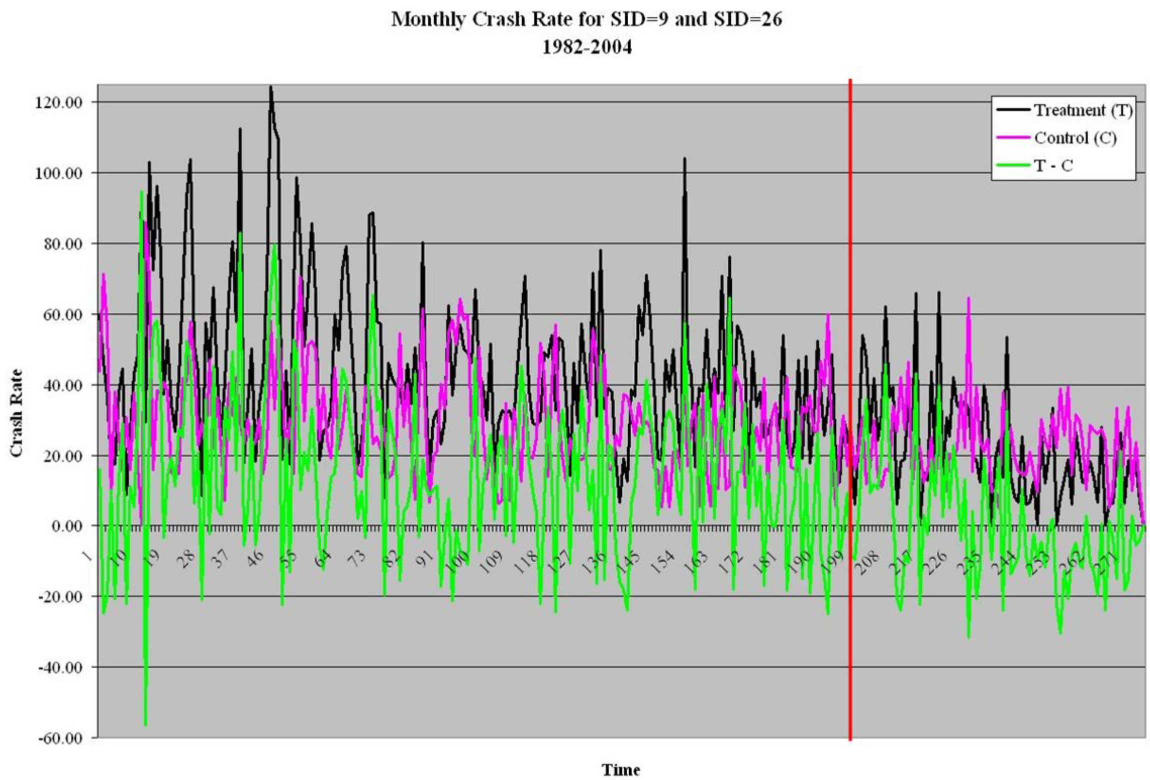


FIGURE 3 Monthly Crash Rate and Difference in Monthly Crash Rate for a Sample Pair of Sites.

In general, as shown by example in Figure 2, both treatment and control site crash history can be seen to experience a reduction. However, the reduction in treatment site crash density and rate after intervention are significantly more marked than at the comparison sites (see Figure 2 for density and Figure 3 for rate). This differs from a previous 4-lane to 3-lane study (2,3,4), recently published in an ITE Journal, whose data, even from a descriptive statistics standpoint, indicated very little reduction or difference between the two groups. Additionally, because monthly crash densities were used for analysis, it was possible to account for the seasonality effects on crashes, which should be expected given the seasonal weather patterns in Iowa.

MODELING

Given the random and rare nature of crash events, a hierarchical Poisson model where the log mean rate was expressed as a function of time period, seasonal effects, and a random effect corresponding to each site included was fitted to the crash frequencies.

We first assume that monthly crashes are distributed as Poisson random variables with mean equal to rate times MADT, where MADT is the monthly volume and rate is the number of crashes at the site during a month divided by volume. Often, the Poisson mean is then modeled as a Gamma random variable (e.g., Hauer and Persaud (9)). The Poisson-Gamma model has been shown to fit crash data well, but does not easily lend itself to accounting for the potential effect of covariates such as time, season and month of conversion on crash frequency.

Here, we adopt a more general model that allows us to estimate and account for the effect of time, conversion month and season on log crash rate. In the second stage of the model we then let the log rate be a piecewise linear function of time, where the change-point (or point where the linear segments join) is located at the month of completion of the intervention in treatment sites. For comparison sites, we located the change-point at the same month as we did in the corresponding paired treatment site.

The monthly crash data clearly showed seasonal effects, as would be expected in Iowa. We defined four seasons: winter (December, January and February), Spring (March, April and May), Summer (June, July and August) and Fall (September, October and November). To account for seasonality in crash rate, we included three smoothly evolving cyclical functions of season with different period and frequency, to capture the smooth and repeating seasonal trends.

Finally, because sites in the study represent a random sample of similar sites in Iowa, a random effect corresponding to site was also included in the model for log crash rate. The random effect was assumed to be normally distributed with mean zero and unknown variance representing the between-site variability in crash rates.

The use of a piece-wise model, sometimes also known as a change point model, to analyze before/after studies has not yet received much attention in the traffic safety literature. Essentially, a change point model assumes that the evolution of crash rates over time before the completion of the intervention is different from the evolution after intervention. Inspection of the observed crash frequencies suggests that crash rates have decreased at the study sites over the past several years. The change-point model allows us to quantify the differences in the slopes of log crash rate on time before and after the conversion. Because some sites were treated and some were not, we included different before and after slopes for treated and comparison sites.

We adopted a fully Bayesian approach (49,40) to estimate model parameters. In the Bayesian approach, model parameters are treated as random variables and the goal is to estimate the distribution of likely values of the parameters given prior and data information. The approach differs from classical methods in that distributions of likely values, rather than point estimates and standard errors of parameters are obtained, and in that all results are conditional on the sample at hand. One other fundamental difference between the classical and the Bayesian approaches to estimation is that prior information about model parameters can be combined with information contained in the sample to draw inferences. This is not possible within the classical framework. The EB approach (23) is a special case in the Bayesian paradigm where prior distributions are partially based on the sample. The distribution of likely values of model parameters on which all inferences are based is known as the joint posterior distribution.

To conduct a Bayesian analysis, we must choose prior distributions for all parameters at the third level of the model. We used proper, semi-conjugate but diffuse priors for two reasons. First, proper priors guarantee that the joint posterior distribution will be integrable. By letting the priors be non-informative (or almost non-informative) we let the data "speak for themselves". In this study, the number of observations available for each site, as well as the number of sites was large enough to assume that the priors will have little if any influence on the posterior distribution. We chose normal prior distributions for all regression coefficients in the log crash rate model, with mean zero and large variance, reflecting the belief that a priori none of the covariates in the model may be associated to the log crash rate. Prior uncertainty about this value is large since the prior variance for the regression coefficients was fixed at 1,000. The between-site variance was assumed to be independent of the regression coefficients a priori and was associated to a scaled-inverted chi-squared distribution. The prior expected value of the inverse between-site variance was assumed to be 1and its prior variance was set at 100 to reflect lack of precise knowledge.

PARAMETER ESTIMATION

We estimated the posterior distributions of the parameters in the model and of functions of model parameters using Markov chain Monte Carlo (MCMC) methods and the freeware WinBUGS (50, 51). For each parameter, we ran two parallel chains over 200,000 iterations. Each chain was burned at iteration 100,001, and to avoid autocorrelation of the parameter draws, we thinned the chains, keeping every 100^{th} draw for inference. We monitored convergence of the chains using the Gelman-Rubin statistic (52) and also checked the autocorrelation functions. That is, we obtained 2,000 almost independent draws from the marginal posterior distributions of each parameter in the model.

Monte Carlo estimates of quantities of interest including means, standard deviation, and various percentiles of the marginal posterior distribution of each parameter were obtained from the draws. For example, posterior means were estimated as the averages of parameter draws over the 2,000 iterations. Similarly, posterior standard deviations are estimated as the empirical standard deviations of draws over the 2,000 iterations.

To assess the effect of the four-lane to three-lane conversion we compared log crash rates in the before and the after periods in treatment and comparison sites. To do so, we had to compute the marginal posterior distributions of linear combinations of the regression coefficients in the model. One advantage of implementing a Bayesian analysis using MCMC methods is that posterior distributions of functions of model parameters can be readily computed from the draws.

RESULTS

Overall, results indicate a 25.2 percent (23.2% - 27.8%) reduction in crash frequency per mile and an 18.8 percent (17.9% - 20.0%) reduction in crash rate over the 15 treatment sites when compared with the control sites. The values in parenthesis are the posterior 2.5^{th} and 97.5^{th} percentiles of the appropriate distributions and constitute a central 95% credible set. That is, with 95% probability, the true reduction in crash frequency per mile is between 23.2% and 27.8%, for example. These results are supported visually by Figures 4 and 5.

Figure 4 shows, for an example pair of sites, the posterior mean of the expected yearly crash density and the 2.5^{th} and 97.5^{th} percentiles of the posterior distribution of crash frequency. The solid vertical lines on each plot mark the year of completion of the intervention at the treated sites.

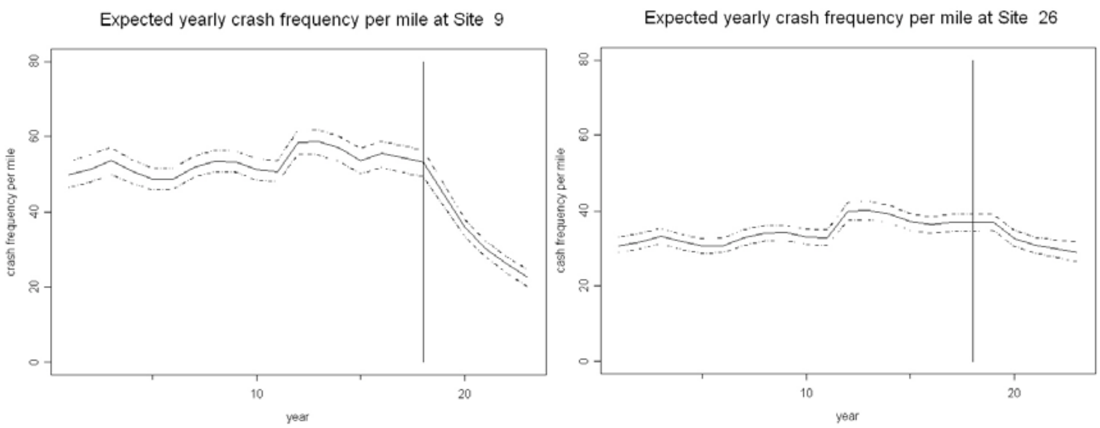
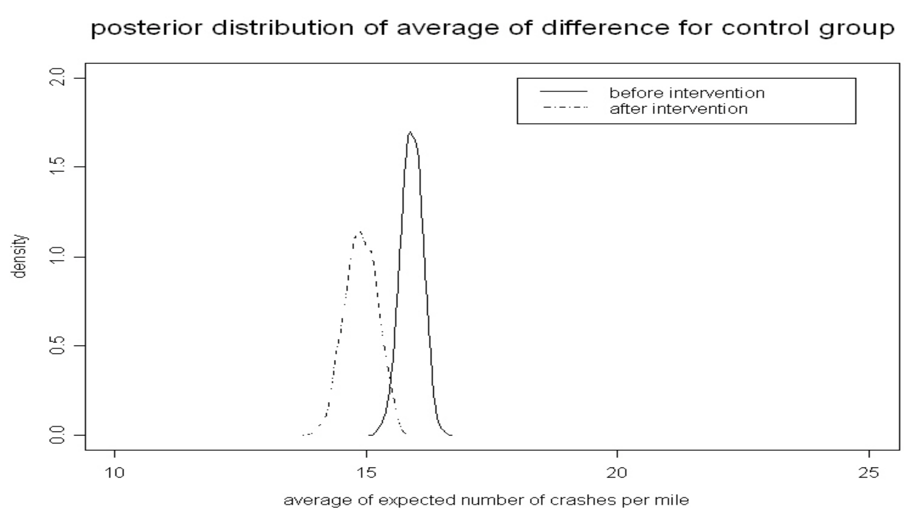


FIGURE 4: Posterior Mean and 95% Credible Set of the Expected Crash Frequency per Year and Mile for Each Site in the Study. Years Preceding the Completion of the Intervention are to the Left of the Vertical Line in
Each Plot.

From Figure 4, we see that there was an estimated reduction in crash density at these sites. The reduction appears to be more pronounced at the treatment site. Notice that the 95% credible sets for expected crash frequencies are in general rather narrow. Thus, we are confident that site-specific expected annual crash frequency per mile is estimated with a good degree of confidence.

We also computed the posterior distribution of expected annual crash densities for all treated and all control sites over the years preceding and following the intervention. The four posterior distributions are shown in Figure 5. From Figure 5, note that while the expected annual crash density has decreased at all sites, the reduction is significantly more pronounced at sites that underwent the conversion. The posterior distributions shown in Figure 5 are narrow, indicating that the posterior mean is a reliable summary of the distribution of likely values of expected crash frequencies.



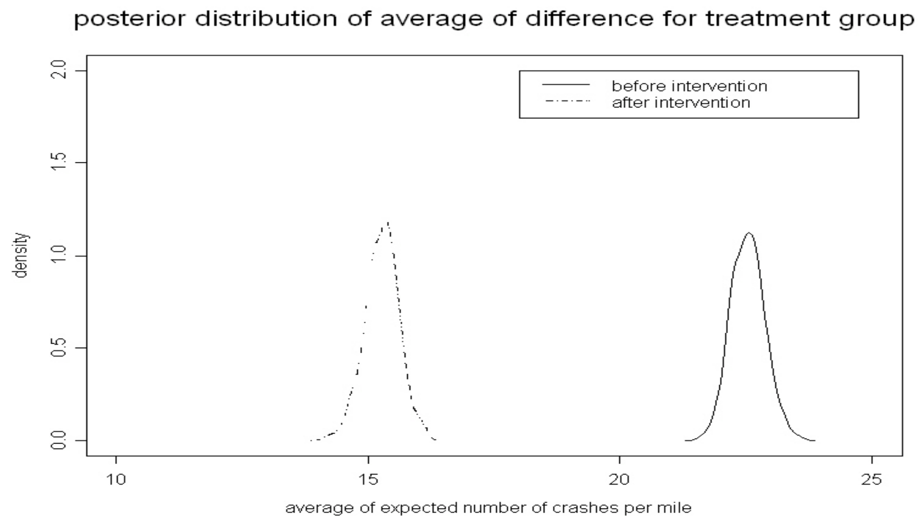


FIGURE 5 Posterior Distributions of the Average (Across Treated and Control Sites) Expected Annual Crash Frequencies per Mile During the Years Preceding and Following the Completion of the Intervention.

Note also that in the control group, the two posterior distributions overlap somewhat, indicating that the reduction in crash density in the after period, while noticeable, is not overwhelming. In contrast, the posterior distribution of average expected crashes per mile after intervention is shifted significantly relative to the distribution estimated for the period preceding the conversion.

The overall 25 percent and 19 percent results differ from the Huang study (2,3,4) which reported a 6 percent reduction in crash frequency per mile and an insignificant indication for crash rate effects. This difference is evident just by comparing the raw data from the two studies. The Iowa data, when graphed, indicates marked reductions whereas the Huang data indicate very little difference. Based on these Iowa FB results and results from a simple before/after analysis done as part of a separate causal study, we are comfortable with the 25 percent and 19 percent reductions, especially as they fit practitioner expectations. A previous study on the same sites by the Iowa State University-based Center for Transportation Research and Education (CTRE) which utilized a simple before/after method with comparison groups indicated a 24 percent reduction in crash frequency due to "road diet" implementation (5). This CTRE study also determined that injury crashes were reduced 34 percent and reductions in crash involvement by younger and older drivers.

Other benefits shown from a previous internal Iowa study on speeds, travel times, and delays on the Sioux Center conversion during AM and PM peak periods, indicate a 4-5 mph reduction in 85^{th} percentile free flow speed and a 30-point reduction in percentage of vehicles traveling more than 5 mph over the speed limit (i.e., vehicles traveling 35 mph or higher) (7,8).

DISCUSSION

The differences between our analysis and the analysis performed by Huang (2,3,4) are several and may explain the diverging results.

First, even the descriptive analysis of the "raw" data suggests that the effect of conversion in Iowa roads was much more dramatic than in the roads considered in the Huang study. Though we adopted a Bayesian approach throughout, a classical analysis could have been conducted and would have resulted in similar point estimates for model parameters. However, a classical analyst would have encountered some difficulties in estimating the variances of parameter estimates in the nonlinear model and would have had to resort to asymptotic approximations.

Second, Huang fitted an ordinary linear regression model to the expected crash frequencies, meaning that a single slope for expected frequency on time was assumed for the entire study period. We extended the model and allowed for different slopes during the "before" and the "after" periods explicitly by including a change-point in the model and for the interaction of treatment and slope. Notice that as a result, our model allows for a slight increase in crash frequency during the months immediately preceding the conversion and also during those months immediately following the conversion.

We fitted a hierarchical Poisson regression model to the crash frequency observed at each site. The log monthly crash rate per mile at each site was then modeled using a piecewise linear regression model with a change-point. The independent variables (or explanatory variables) in the change-point regression included the effects of the four seasons of the year, treatment, time and interactions of treatment and time. To estimate the association between log monthly crash rates and the explanatory variables, we added a random effect to account for overdispersion and for autocorrelation among observations obtained at the same site. We used proper but non-informative priors for all parameters in the model, and carried out all calculations using Markov chain Monte Carlo methods implemented in WinBUGS. Our model permits accounting for temporal variation in traffic volume (e.g., Hauer (23)) and also for the effect of season on crash frequency.

Finally, we included a longer time series of crash frequencies as we included 23 years of data on almost all sites in the study. By analyzing monthly data, we were also able to account for seasonal variability in crash frequency and traffic volume; while a "must" in Iowa, where seasonal variation in driving conditions is marked, this may not be as critical in a study conducted in the northwestern region of the country. Huang's study, though it began with 12 treatment sites and 25 control sites was reduced to 8 treatment sites and 14 control sites for the crash rate analysis due to unavailability of data. Additionally, Huang utilized only 3 years of data for both the before and after period.

One potential improvement to our analysis might be the inclusion of a "buffer" period around the time of conversion of the site during which drivers get used to the new layout of the road. Huang (2,3,4) accounted for this effect by ignoring crashes that occurred around the time of conversion. We included all crashes in our analysis and attempted to account for the potential impact of the conversion itself with a model parameter. It may be better to proceed as in Huang (2,3,4) and remove crash information around the conversion time from the analysis dataset. We do not anticipate noticeable differences in our results even if we re-analyze the data omitting some of the monthly crash records.

FUTURE RESEARCH

Further investigations of the topic of "road diet" implementations within Iowa from a FB viewpoint are planned. Much as the CTRE study investigated causal factors, injury severity impacts, and age-related impacts using a simple before/after methodology, these same categories will be approached from an FB viewpoint. Additionally, another researcher had requested these data for an NCHRP effort. This researcher was planning to apply an EB approach to the data.

Further applications of the FB approach to Iowa data are planned. Iowa has also converted several 2-lane sites to 3-lane sites over the past 25 years. Utilizing an approach similar to the "road diet" application, the impacts of these treatments will be similarly investigated. Additionally, Iowa has numerous advanced stop sign rumble strips placed throughout the state. We plan to investigate the potential reduction in types of crashes that might result from installation of these rumble strips.

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